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Mediated influence of digital agriculture technologies on climate-smart agriculture decisions among smallholder farmers in sub-Saharan Africa: a systematic review

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Digital agricultural technologies like remote sensing, geographic information systems (GIS), artificial intelligence (AI), mobile-based advisory services, and the Internet of Things (IoT) potentially promise to enhance smallholder farmers' climate-smart agriculture (CSA) adoption decisions in sub-Saharan Africa (SSA). This study examines how digital technologies influence smallholder farmers' decision-making regarding the adoption of climate-smart practices in SSA, focusing on identifying key technological pathways that enhance adaptive capacity and resilience to climate change. The study explored the role of digital agricultural tools in influencing CSA adoption. A critical analysis of 82 selected peer-reviewed articles published between 2015 and 2025 was conducted, identified through academic databases including Scopus, Web of Science, and Google Scholar. The review synthesized findings to identify consistent pathways through which digital tools support climate adaptation and agricultural resilience. Results indicate that digital technologies influence decision-making through three pathways: real-time information provision using IoT sensors and remote sensing, predictive analytics for climate risk assessment using artificial intelligence and machine learning, and optimized timing of farm operations through digital advisory and early warning systems. Empirical evidence shows improvements in resource use efficiency, yield stability, and climate risk preparedness using decision-support tools, although adoption remains constrained by barriers such as limited digital literacy, infrastructural challenges, affordability constraints, institutional capacity, social fabric limitations, and gender inequality. We conclude that digital technologies significantly enhance CSA adoption by reducing uncertainty and improving farm-level decision-making, although investment in infrastructure, digital literacy, and institutional support remains critical for scaling sustainable climate adaptation outcomes.

KEYWORDS
climate-smart agriculture, decision-making, digital agriculture, smallholder farmers, sub-Saharan Africa

1 Introduction

1.1 Climate change and smallholder agriculture in sub-Saharan Africa

Climate change substantially jeopardizes food systems worldwide, and sub-Saharan Africa (SSA) bears the brunt of climate variability despite its minimal contribution to greenhouse gas emissions. The region is home to about 77 million smallholder farmers (Lowder et al., 2016), constituting 80% of the total farming population (IFAD, 2014). Surprisingly, less than 5% of sub-Saharan Africa's arable land is supported by irrigation infrastructure (Wiggins and Lankford, 2019; You et al., 2011). This means that agricultural production is overwhelmingly rain-fed, with reports indicating that 95% of smallholder farmers rely on natural rain for their farming activities (Abrams, 2018; Dadzie et al., 2024)—hindering their productivity and resulting in food insecurity.

Most farmers typically operate on less than two hectares of land and are the most vulnerable to climatic risks, yet they constitute the backbone of food security in the region (Lowder et al., 2016; Ricciardi et al., 2018). Climate shocks such as elevated temperatures, erratic precipitation, and frequent weather events threaten the region's agricultural productivity (Manono et al., 2025; Mutengwa et al., 2023). Over the decades, farming has evolved from rudimentary methods to more technology-oriented production. For instance, the emergence of climate-smart agriculture (CSA) integrates approaches to transform agricultural systems by leveraging available knowledge and innovation to reduce emissions, enhance productivity, foster resilience, and elevate food security (Kabato et al., 2025; Ariom et al., 2022). Such approaches include conservation agriculture, agroforestry, improved water management, drought-resilient crop varieties, and integrated soil fertility management, among other practices (Ariom et al., 2022; Oyelami et al., 2023).

1.2 The digital agriculture promise

Beyond the development of climate-smart agriculture, advancements in digital technology have opened new frontiers for agricultural decision-making (Mollel et al., 2025; McFadden et al., 2022). These advancements hold transformational potential for smallholder farmers by facilitating resource optimization through data-driven decisions (Mhlanga and Ndhlovu, 2023). As Basso and Antle (2020) argue, digital agriculture offers pathways to designing sustainable agricultural systems through precision technologies that optimize resource use while maintaining productivity. Incorporating digital technologies in farming systems directly assists farmers in transitioning from reliance on traditional farming practices to embracing precision farming for sustainability, enhanced productivity, and resilience (Alsanhani et al., 2025; Assimakopoulos et al., 2024; Abdulai et al., 2023).

Technologies such as remote sensing, incorporating satellite imagery and drone-based sensors, foster monitoring of crop vigor, soil conditions, and water availability at spatial and temporal scales (Onyango et al., 2021; Nyaga et al., 2021), thereby helping farmers make informed decisions on the most appropriate actions to take. According to FAO (2019), reducing food loss and waste through such digital technologies is critical for sustainable agricultural systems, while Mekonen (2025) demonstrates that AI-powered decision support systems in Ethiopia have enabled smallholder farmers to optimize input use and improve productivity through real-time data from remote sensing and IoT devices. Geographic information systems (GIS)-based tools like ArcGIS or QGIS software enable spatial analysis of farming terrains and provide resource optimization and site-specific management recommendations (Fetene, 2021). Internet of Things technologies such as soil sensors, weather stations, and automated irrigation systems offer real-time data on field conditions, allowing farmers to make responsive management decisions (Ayaz et al., 2019; Tzounis et al., 2017; Bacco et al., 2019; Rajak et al., 2023; Gatkal and Sharma, 2024).

Conclusively, these technologies support decision-making in three practical ways. For instance, they provide real-time data on soil moisture content and crop vigor, informing targeted fertilizer application (Kuradusenge et al., 2024; Bayih et al., 2022). Similarly, smart irrigation systems (Nigussie et al., 2020) initiate early warning for climate risks such as floods and pest invasions (Mmbando, 2025; Foster et al., 2023), supporting climate modeling that enables long-term planning (Bashiru et al., 2024) and linking farmers to weather-index insurance and carbon markets (Shaibu et al., 2025).

1.3 Digital agriculture in the sub-Sahara African context

sub-Saharan Africa possesses prospects for digital agriculture among its farming population; however, the region faces unique drawbacks to the adoption of digital agriculture technology due to several factors, including infrastructural limitations, economic constraints, social and cultural considerations, and institutional rigidity (Chepkemoi et al., 2025; Chisanga et al., 2025; Tsan et al., 2019; Mhlanga and Ndhlovu, 2023). Despite the region's high potential and significant number of smallholder farmers, challenges such as poor internet coverage and low digital literacy limit accessibility to technologies (Cariolle, 2021; Jellason et al., 2021; GSMA, 2021; Bontsa et al., 2023).

Economically, the region lags behind in the adoption of digital agriculture, as most farmers are resource-poor, face expensive digital tools, and have limited access to credit facilities, resulting in challenges of affordability (Onyango et al., 2021; Addison et al., 2024). The region also has its share of societal-induced challenges, including social constructs like gender differentiation, reliance on local knowledge, and limited digital knowledge, all of which undermine technology acceptance (Khoza et al., 2021; Thothela et al., 2021; GSMA, 2022; Leta et al., 2023). Additionally, weak extension services that lack technical support and disjointed policies hinder technology promotion and sustainability in sub-Sahara Africa (Ayim et al., 2022; Habiyaremye et al., 2024).

1.4 Research gap and unique contribution of the study

Despite rapid development, sustained promotion, and growing interest in digital agriculture, significant gaps remain in understanding how remote sensing, GIS, and IoT technologies practically influence the adoption decisions of CSA among smallholders in SSA (Jellason et al., 2022; Nyaga et al., 2021).

This review identifies three critical gaps that justify the need for the present study:

1.4.1 Lack of integrated influence mechanisms

Existing research tends to examine individual technologies in isolation, failing to synthesize how different digital tools collectively shape decision-making processes (Choruma et al., 2024; Nyaga et al., 2021). Choruma et al. (2024) note in their scoping review of digitalization in African agriculture that there is limited integration across technology types in understanding farmer decision-making outcomes. Similarly, Onyango et al. (2021) observed that precision agriculture studies in SSA typically focus on single technologies without examining how combinations of tools interact to influence farmer behavior. Klerkx and Rose (2020), Geels (2019), and Ayim et al. (2022) further emphasize that technology adoption studies often treat tools as discrete interventions rather than integrated systems. Few studies provide a comprehensive framework that explains the pathways through which remote sensing, GIS, and IoT technologies translate data into farmer action.

1.4.2 Limited attention to contextual determinants

While adoption constraints are frequently mentioned, the interconnected nature of infrastructure, economic, institutional, and gender barriers remains undertheorized (Mhlanga and Ndhlovu, 2023; Bontsa et al., 2023). Khoza et al. (2021) emphasize that gender barriers intersect with other constraints to enhance systemic exclusion, yet integrated analysis remains rare. Zougmoré and Partey (2022), GSMA (2022), and Appiah et al. (2025) further document that gender disparities compound other barriers to technology adoption. Bashiru et al. (2024) similarly note that most adoption studies treat barriers as independent rather than interconnected, limiting understanding of why technologies succeed in some contexts but fail in others. It is therefore essential to understand how these factors interact to create systemic exclusion when designing effective interventions.

1.4.3 Absence of scalability analysis

The literature predominantly features pilot studies with limited attention to what enables or constrains scaling (Kreft et al., 2023). The persistent “pilot-to-scale” gap, where successful demonstrations fail to achieve widespread adoption requires systematic investigation. Jellason et al. (2021) highlight that “most digital agriculture interventions in SSA remain at pilot scale, with limited evidence on what drives successful scaling.” Rurii and Nzengya Daniel (2026) further emphasize that “without understanding scaling mechanisms, technology adoption remains episodic rather than transformative.” Choruma et al. (2024) and Appiah et al. (2025) document that fewer than 10% of digital agriculture initiatives scale beyond pilot projects.

This review offers a novel integrated socio-technical framework that bridges the gaps between technical potential and practical reality, drawing on socio-technical literature (Geels, 2019) and adaptation pathways approaches (Sietz et al., 2022). Unlike existing reviews that focus solely on climate impact or digital tools in isolation, we (i) synthesize evidence across four technology types (remote sensing, GIS, IoT, and ML) to identify common influence pathways while systematically analyzing the interconnected barriers that shape adoption outcomes; (ii) integrate evidence across these technology types using a unified framework; and (iii) map the interconnections between infrastructural, economic, institutional, and gender barriers, analyzing the pilot-to-scale gaps as a design problem requiring systematic solutions. Our framework explicitly connects climate resilience with socio-economic and structural factors, such as the digital divide, gender inequality, and policy gaps that determine whether the technology reaches and benefits the most vulnerable farmers (McFadden et al., 2022). This integrated perspective provides researchers, practitioners, and policymakers with a holistic understanding of both the promise and the present challenges of digital agriculture in SSA. The main aim extends beyond documenting negative climate impacts to examining how digital technologies function as both affected by and solutions to climate challenges, consistent with the dual farming advanced by Zougmoré et al. (2021) and Partey et al. (2020).

2 Materials and methods

2.1 Protocol and registration

The review followed a detailed guideline of Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol Page et al. (2021) to ensure transparency and reproducibility. The review outlines clear steps for the systematic identification, selection, and synthesis of relevant information from past publications. Due to the nature of the review, no protocol was registered in PROSPERO.

2.2 Scope of the study

2.2.1 Implementation of digital agriculture technology

The study focuses on the practical application and use of digital technologies, particularly remote sensing, geographic information systems, and the Internet of Things, in a smallholder farmers' setup confined to actual in-field settings and in an on-farm study site within sub-Saharan Africa.

2.2.2 Influence on decision-making

The precise aim of the study lies in understanding how the application of these digital technologies informs the decision-making processes of smallholder farmers to adopt climate-smart agriculture practices. The study is limited to evidence indicating smallholder farmers actively engaged with these technologies, as opposed to scenarios where farmers are sidelined or reduced to being observers.

2.2.3 Methodology

This study focuses on primary research demonstrating methodological rigor, including qualitative, quantitative, or mixed methods, as well as systematic reviews and meta-analyses where empirical data is synthesized. Any study that theorizes the use of these technologies without a farmer focus was excluded.

2.3 Search strategy

The study conducted a detailed search spanning multiple databases, including Google Scholar and Web of Science, following the search strategies recommended by Lefebvre et al. (2019) for systematic reviews. A combination of key words including “remote sensing,” “GIS,” “geographic information system,” “IoT,” “internet of things,” “climate-smart agriculture,” “CSA,” “smallholder farmers,” “small-scale farmers,” “decision-making,” “adoption,” and “sub-Saharan Africa” informed the search strategy. The research focused on papers published only between 2017 and 2025 in English to capture the most recent evidence. The review further applied Boolean Operators to search for article titles with the following specific search strings: (“remote sensing” OR “GIS” OR “geographic information system OR "IoT" OR "internet of things") AND ("Climate-smart Agriculture" OR "CSA") AND ("smallholder farmer" OR "small-scale farmer") AND ("Decision-Making" OR "Adoption") AND ("sub-Saharan Africa" OR "Africa"). The combination of terms using Boolean Operators aimed to maximize search sensitivity from the databases.

2.4 Eligibility criteria

The study type in this review included only peer-reviewed articles from journals, doctoral theses, institutional reports, grey literature, and conference proceedings published between 2017 and 2025.

2.4.1 Inclusion criteria

The study considered materials intended for analysis based on the following tenets:

Population: Studies solely focusing on smallholder farmers in sub-Saharan Africa potentially predisposed to climate risks.

Technology intervention: Studies examining the application of remote sensing, GIS-based tools, and IoT technologies in agricultural settings.

Decision-making outcomes: Studies reporting mechanisms of how technologies influence the decision-making process for adopting climate-smart agriculture.

Study type: Empirical research employing qualitative, quantitative, mixed-methods, case studies, and systematic reviews informed the inclusion criteria, rather than opinion pieces or purely theoretical papers.

Publication quality: Studies published in peer-reviewed academic journals, conference proceedings, and credible institutional reports.

Publication period: Studies published in English between 2017 and 2025.

2.4.2 Exclusion criteria

Studies were excluded if they.

- Were published before 2017,
- Lacked methodologies or presented general conclusions,
- Focused on technology types other than GIS, IoT, and remote sensing,
- Lacked publication dates, authors, and were in other languages,
- Did not focus on smallholder farmers and were confined outside of sub-Saharan Africa.

2.5 Screening process

An initial search generated from four databases (Scopus, Web of Science, Science Direct, and Google Scholar) yielded 9,246 potential studies, which were subjected to data cleaning by removing duplicates (3,918). This resulted in 5,328 records, which were screened by title and abstract. Upon screening, 4,892 records were excluded for various reasons, allowing a full-text review of 436. The full-text review generated 76 records. The review also retrieved 10 records from other sources, assessed their eligibility, in which 4 records were excluded while 6 passed eligibility tests. At the end of the screening, 82 studies were ultimately included for synthesis (Figure 1).

2.6 Data extraction mechanism

Data extraction employed a standardized framework developed to capture:

- Study characteristics: Author, year, geographic niche, methodology, and key findings.
- Technology focus: Type of remote sensing, GIS, and IoT technology examined.
- Decision-making influence: Mechanism and evidence of influence on farmer decisions.
- CSA practices examined: specific practices and reported adoption rates.
- Adoption determinants: Enablers and barriers characterized by factor type.
- Integration approaches: how technologies were deployed and what support systems were used.
- Contextual factors: socio-economic, infrastructural, and institutional conditions.

The study used the Scispace AI data extraction tool to ensure accuracy, with all extracted data verified manually by the authors.

2.7 Data synthesis

The thematic synthesis of data included organizing the information into key domains identified in the research question. Given the heterogeneity in study designs, technology types, and outcome measures, the review conducted a narrative synthesis following Petticrew and Roberts (2008)'s guidance for narrative synthesis in systematic reviews and recommendations for complex policy-relevant reviews. Thematic analysis organized the data into key domains identified in the research questions, with patterns and relationships identified across studies.

3 Results

3.1 Characteristics of included studies

The review included 67 sources published between 2017 and 2026. Geographically, the studies covered 15 multi-country analyses and 15 individual sub-Saharan African countries, with South Africa (9), Kenya (8), Ethiopia (7), and Ghana (6) being the most represented. In terms of regional representation, East Africa registered the highest number of studies (21), followed by Southern Africa (18) and Western Africa (14). Central Africa is notably absent from the single-country studies. The multi-country studies (16) take a regional or continental perspective, providing valuable cross-country comparison and synthesis. The review synthesizes the included studies by geographic focus, outlining the country or region, the number of studies conducted in specific countries or multiple countries, the methodology applied in each study, and representative authors, as shown in Table 1 and Figures 2, 3.

3.2 Remote sensing, GIS, and IoT technologies

An overview of the main technology types examined in the review is provided in Table 2. The table details the specific technologies, their

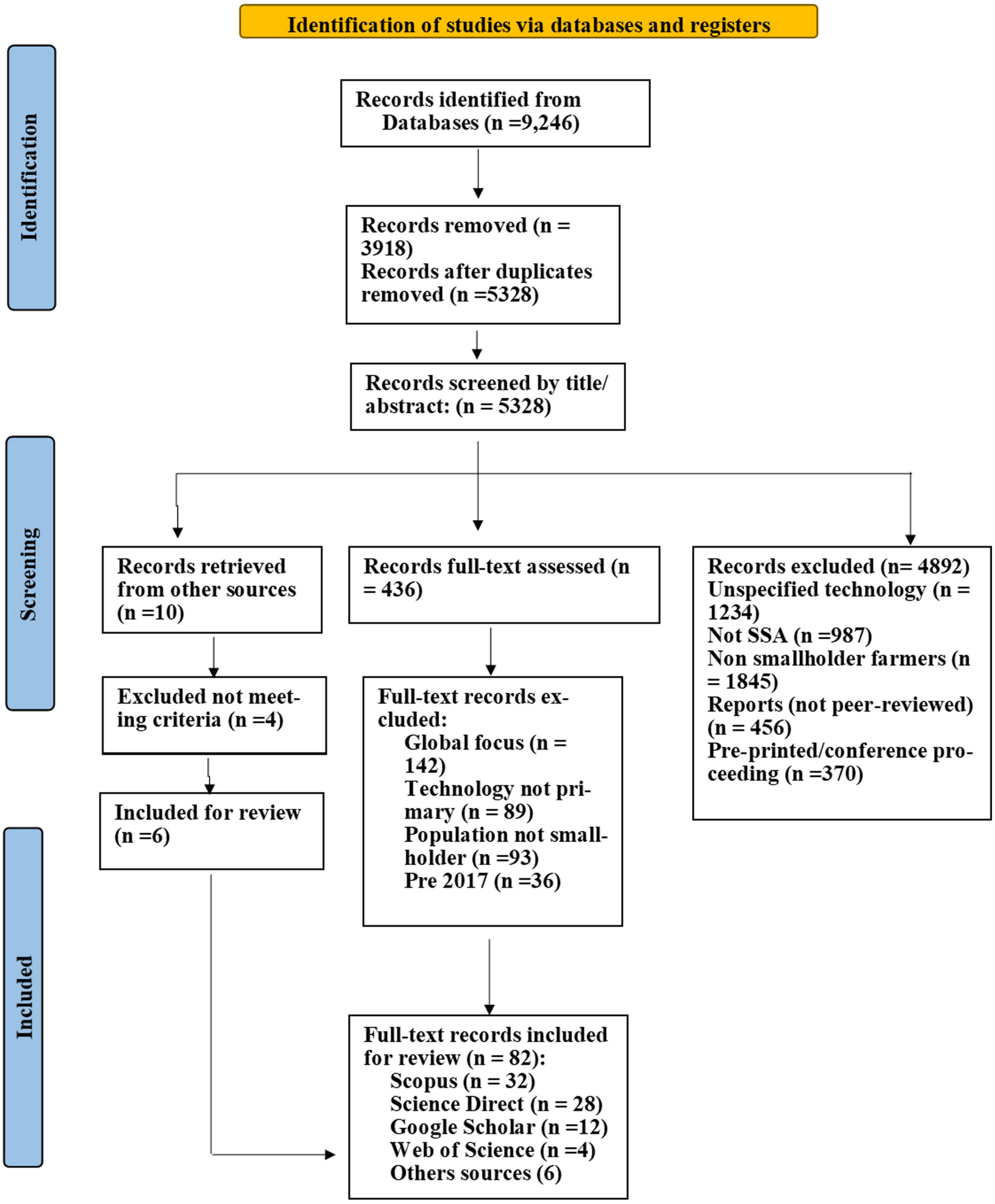

FIGURE 1
PRISMA flow diagram for screening process.

respective applications in the agricultural sector, and examples of studies where they have been utilized (Table 3; Figures 4, 5).

3.3 Technology application trend in SSA

The graph shows a clear upward trajectory, with a notable surge after 2023 in sub-Saharan Africa. This aligns with the global shift toward agriculture 4.0, climate-smart digital solutions, and increased investment in agri-tech for smallholder farmers (Figure 6).

3.4 Quality assessment of included studies

The quality of included studies was assessed using adapted criteria from the Risk-Of-Bias Visualization (ROBVIS) checklists (Mcguinness, 2020). Studies were rated as low risk (*n* = 69), some concerns (*n* = 12), or high risk (*n* = 0) based on methodological rigor, sample representativeness, and clarity of reporting. The four high-risk studies (Tzounis et al., 2017; Liakos et al., 2018) are global-focused reviews that provide contextual background but are not directly applicable to SSA-specific conclusions. Low-quality (high-risk) studies were retained but given less weight in the synthesis (Figures 7, 8).

3.5 Influence on decision-making processes

The synthesis reveals three pathways through which remote sensing, geographic information systems, and Internet of Things technologies influence smallholder farmers' decision-making for climate-smart

TABLE 1 Summary of included studies by region.

Country/region	Number of studies	Methodology used	Representative author
Ghana	6	Quantitative surveys, mixed-methods	Shaibu et al. (2025), Bismark et al. (2021), Asante et al. (2024), and Moomen et al. (2024)
Kenya	8	Systematic review, book chapter, review	Mmbando (2025), Manzi and Gweyi-Onyango (2021), Muthoni (2023), Wahome et al. (2023), Chepkemoi et al. (2025), and Njuguna et al. (2025)
Nigeria	3	Quantitative survey, experimental design	Bashiru et al. (2024), Okoh et al. (2023), and Adenubi et al. (2021)
South Africa	9	Geospatial analysis, quantitative survey, conference paper	Thothela et al. (2021), Serote et al. (2023), Abegunde et al. (2019), Mpakairi et al. (2023), and Mashaba-munghemezulu and Chirima (2021)
Tanzania	5	Literature review	Mushi et al. (2022) and Ayaz et al. (2019)
Ethiopia	7	Systematic review, geospatial analysis	Getahun et al. (2024), Fetene (2021), and Bayih et al. (2022)
Rwanda	5	Experimental design, case study	Kuradusenge et al. (2024) and Chavula and Kayusi (2025)
Zambia	2	Quantitative survey	Petros et al. (2025)
Mozambique	3	Spatial econometrics	Fang and Richards (2018)
Uganda	2	Preprint	Nomugisha and Mwebaze (2025)
Senegal	1	Project report	Beckie et al. (2022)
Malawi	2	Quantitative survey	Khoza et al. (2021)
Mali	1	Digital advisory service	Kante et al. (2019)
Burkina Faso	1	Quantitative survey, remote sensing	Karst et al. (2020)
Multi-country SSA	16	Systematic reviews, quantitative analysis	Bashiru et al. (2024), Onyango et al. (2021), Jellason et al. (2021), Choruma et al. (2024), Ayim et al. (2022), Rurii and Nzengya Daniel (2026), Zougmoré and Partey (2022), Appiah et al. (2025), and Chisanga et al. (2025).
			Choruma et al. (2024), Lebourgeois et al. (2017), Js et al. (2021), Klerkx and Rose (2020), and Fabregas et al. (2019)

agriculture adoption. These pathways operate at different temporal scales and address different types of agricultural decisions.

3.5.1 Pathway 1: provision of real-time information

IoT-based systems and remote sensing technologies provide continuous, real-time data on soil parameters, microclimate conditions, and water availability (Rajak et al., 2023; Gatkal and Sharma, 2024). This information enables farmers to make evidence-based decisions about irrigation timing, fertilizer application, and planting schedules. Kuradusenge et al. (2024) developed an IoT and machine learning-powered crop yield prediction system in Rwanda, demonstrating how real-time soil moisture and environmental data enabled precision irrigation decisions, leading to improvements in water use efficiency.

Bayih et al. (2022) designed an agricultural decision support system that integrates wireless sensor networks, citizen science, and remote sensing in Ethiopia, demonstrating how real-time data influence farmer decisions through context-aware recommendations delivered via a mobile platform. Okoh et al. (2023) implemented an IoT cloud-based platform for smart farming in sub-Saharan Africa, with smart irrigation as a test case, indicating how real-time sensor data influenced irrigation scheduling decisions. Nomugisha and Mwebaze (2025) proposed a smart IoT framework for climate-resilient maize farming in Uganda, showing how real-time monitoring can guide planting and input decisions. A review by Mushi et al. (2022) validates the pathways proposed by Nomugisha and Mwebaze (2025) and contextualizes the wider hurdles that such frameworks face in sub-Saharan Africa (Ngulube, 2025).

Influence mechanism: Continuous data streams → situational awareness → evidence-based adjustments → optimized resource use.

3.5.2 Pathway 2: risk assessment through predictive analysis

Machine learning algorithms and remote sensing data enable assessments of crop health, disease prevalence, and yield potential, whereas AI-powered analytics forecast weather patterns and pest invasions (Foster et al., 2023; Gatkal and Sharma, 2024). This information supports strategic decisions about variety selection, planting dates, and resource allocation. Mmbando (2025) reviewed how artificial intelligence and remote sensing in climate-smart agriculture support early warning systems and risk assessment, allowing proactive decision-making that reduces crop losses. Shaibu et al. (2025) examined how climate information services influenced smallholder farmers' willingness to invest in CSA practices in Northern Ghana, noting that access to daily or seasonal weather forecasts shapes investment decisions through improved risk perceptions—farmers with forecast access were 2.3 times more likely to invest in drought-tolerant varieties. The potential of digital advisory services in this context is further

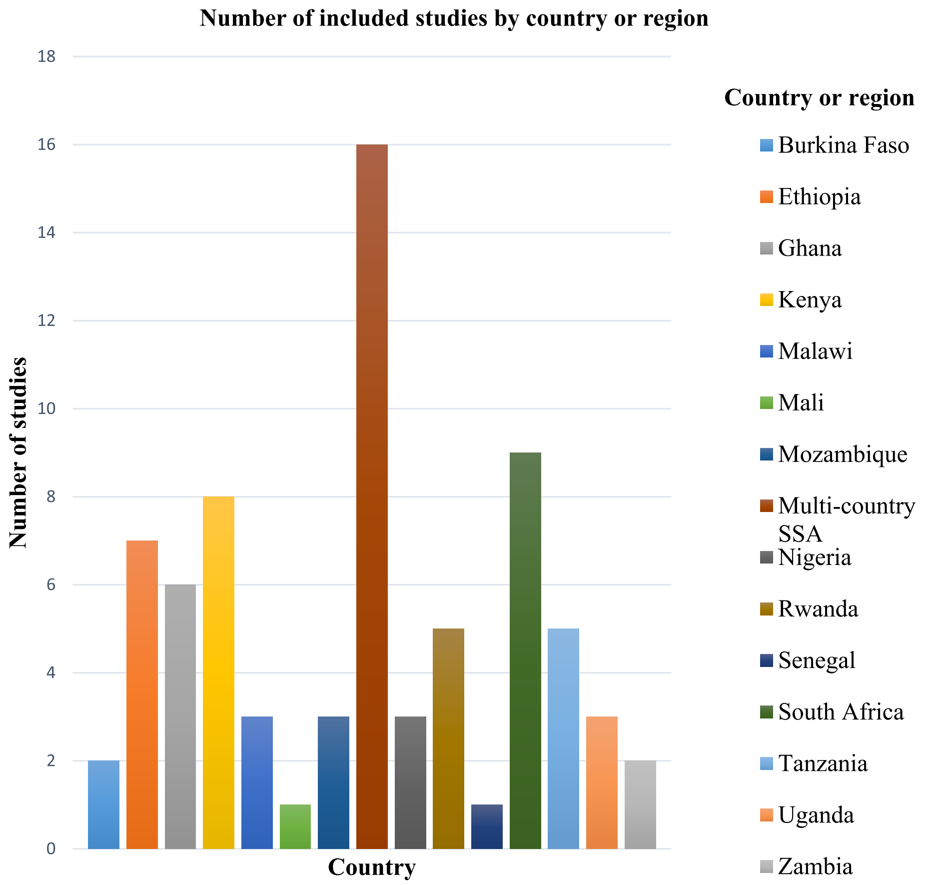

FIGURE 2
Number of studies by country.

supported by Asante et al. (2024), who demonstrated that digital advisory services with predictive information significantly increased the adoption of recommended CSA practices among smallholder farmers in Ghana. Nturo et al. (2025) developed an AI-driven precision agriculture system in Rwanda, demonstrating how predictive analytics enable farmers to make informed decisions about planting times and input applications, with participating farmers reporting improvements in yield. Liakos et al. (2018) demonstrated that machine learning techniques such as random forest, support vector machine, and artificial neural network could achieve high accuracy in yield prediction when calibrated with local datasets.

Influence mechanism: Historic → real-time data → predictive analytics → risk forecasting → strategic planning → proactive adaptation.

3.5.3 Pathway 3: timing through optimized scheduling and early waring

Integrated systems combining indigenous knowledge with sensor data and predictive analytics provide specific recommendations regarding when to plant, irrigate, harvest, or apply inputs, while early warning systems enable proactive responses to climate variability (Oyelami et al., 2023). Thothela et al. (2021) surveyed intelligent agro-climate decision support tools for small-scale farmers, focusing on systems that integrate indigenous knowledge, mobile phone technology, and smart sensors. The study highlighted the ITIKI system for drought prediction as a successful example, incorporating both indigenous observations and sensor data to influence farmer decisions. Farmers using ITIKI reported a reduction in drought-related crop losses. Shaibu et al. (2025) and Dadzie et al. (2024) found that both scientific forecasts and indigenous predictions shaped farmers' decisions, with the integration of both knowledge sources proving more effective than either alone—farmers receiving integrated information were more likely to adopt recommended practices. Nyoni et al. (2024) conducted a review on effective digital-based information service delivery of climate information for smallholder farmers, identifying that timing-specific recommendations achieved higher adoption rates than general advisories. Additionally, Rurii and Nzengya Daniel (2026) carried out a scoping review on the adoption and impacts of climate-smart technologies in Africa, identifying that support tools providing actionable timing guidance significantly outperformed information-only approaches, thus reinforcing the influence of agricultural technologies on farmers' decision-making (Figure 9).

Influence mechanism: integrated knowledge systems (indigenous + scientific) → localized recommendations → actionable timing guidance → precise implementation.

3.6 Adoption determinants: enablers and barriers

The review summarized findings on the key factors affecting the adoption of agricultural technologies and presents a dual perspective, including enablers that drive adoption and barriers that constrain it across seven categories (Teklu et al., 2022; Diro et al., 2022; Musafiri et al., 2022). The framework illustrates the multifaceted

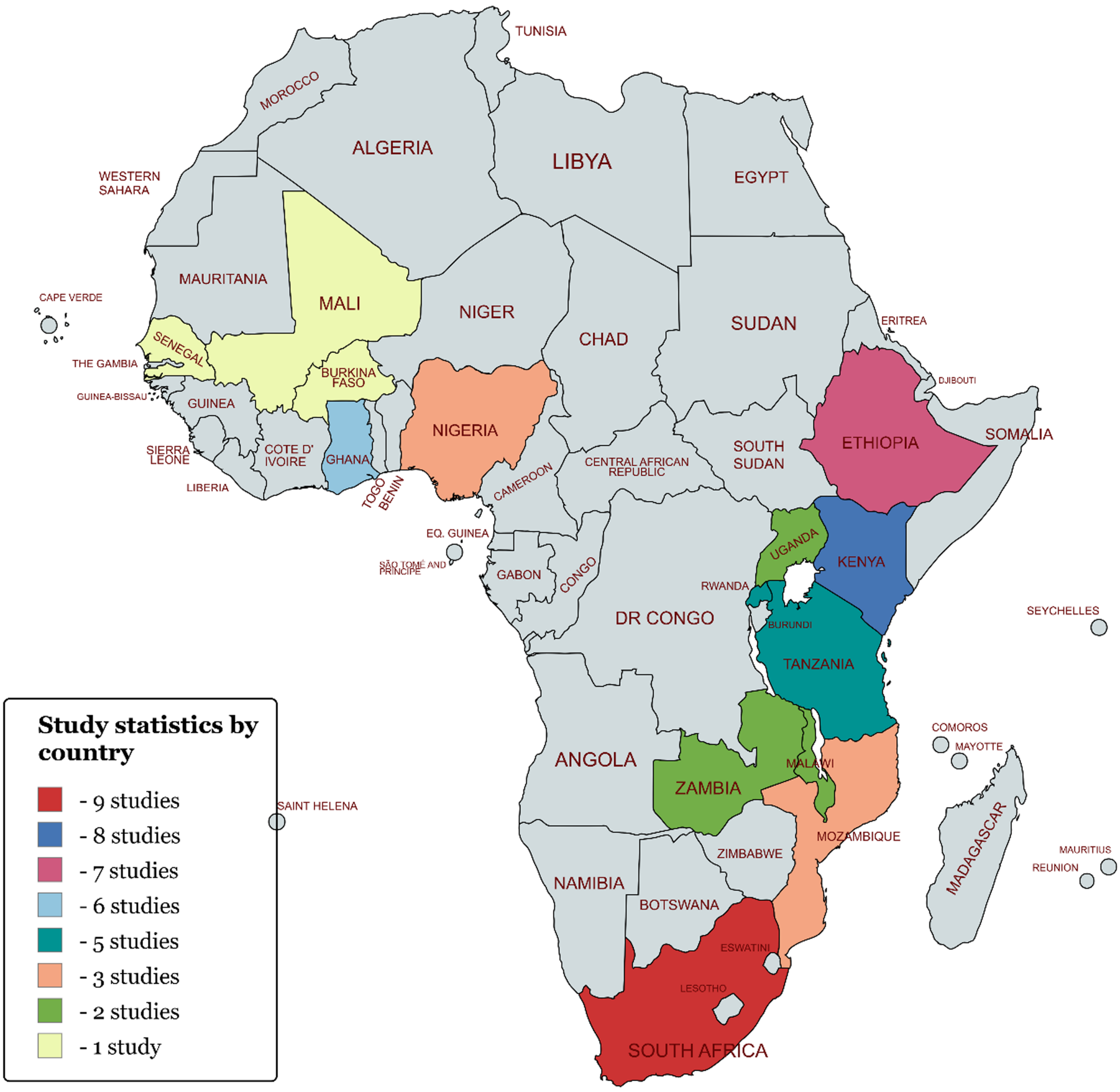

FIGURE 3
Studies by country. Source: MapChart. Africa: Create a custom map. Available online: https://www.mapchart.net/africa.html (accessed on 28 March, 2026).

nature of adoption decisions and the range of factors that need consideration in implementation strategies (Table 4) (Geels, 2019; Kreft et al., 2023).

Infrastructure barriers constitute the fundamental constraint. Cariolle (2021) analyzed international connectivity and the digital divide in sub-Saharan Africa, along with GSMA (2021) and Bontsa et al. (2023) noted that limited broadband infrastructure and high connectivity costs fundamentally constrain digital technology deployment. Similarly, Jellason et al. (2021) assessed sub-Saharan Africa's readiness for agriculture 4.0 (the fourth agricultural revolution transforming the agricultural sector through the integration of advanced digital technology), identifying poor digital infrastructure, unreliable electricity, and high internet costs as the primary barriers to the adoption of remote sensing, geographic information systems, and the Internet of Things in climate-smart agriculture. Mushi et al. (2022) documented similar findings to those of GSMA (2022), noting that even where mobile networks exist, data costs consume 5–15% of monthly household income, making data-intensive applications unaffordable.

Economic barriers compound infrastructural limitations. Bashiru et al. (2024) found that high costs reduced uptake among resource-poor farmers, while access to credit increased the likelihood of adoption by 2.5 times. Onyango et al. (2021) documented that precision agriculture technologies remain unaffordable for most smallholders, with basic sensor kits costing $200-500—an equivalent of 3–6 months of income for average households. Nigussie et al. (2020) noted that while IoT-based irrigation systems demonstrated 30–50% water savings, initial costs prevented widespread adoption. On the other hand, Adenubi et al. (2021) observed that whereas mobile phone penetration has increased, data costs remain prohibitive for data-intensive applications.

Institutional barriers cuts across categories, exacerbating systematic exclusion. In a systematic review on ICT adoption in African agriculture, Ayim et al. (2022) identified extension services as critical facilitators of ICT adoption in Africa, yet they noted that most countries have extension-to-farmer ratios below 1:1,000, severely limiting reach. Onyango et al. (2021) identified technical skill gaps as a major barrier to precision agriculture adoption. Thothela et al. (2021) emphasized the

TABLE 2 Technology types and applications.

Technology category	Specific technology	Applications	Representative studies
Remote sensing	Satellite imagery (Sentinel-2, Pléiades Landsat), drone-based sensors, multispectral imaging, CHIRPS, TAMSAT, SAR	Crop health monitoring (NDVI), yield prediction, land suitability analysis, rainfall monitoring, biomass estimation, invasive species detection, drought assessment	Onyango et al. (2021), Manzi and Gweyi-Onyango (2021), Mmbando (2025), Bismark et al. (2021), Nyaga et al. (2021), Ngulube (2025), Gatkal and Sharma (2024), and Rajak et al. (2023)
GIS-based tools	Spatial analysis software (ArcGIS, QGIS), digital soil mapping, land suitability modeling, mobile GIS apps	Site-specific management recommendations, land-use planning, extension mapping services, resource allocation, water harvesting site selection, extensive service delivery mapping, crop selection optimization	Fetene (2021) and Fang and Richards (2018)
IoT technologies	Soil moisture sensors, weather stations, automated irrigation systems, LoRaWAN networks, wireless sensor networks	Real-time monitoring, precision irrigation, climate data collection, automated control systems, network performance evaluation	Kuradusenge et al. (2024), Bayih et al. (2022), Nomugisha and Mwebaze (2025), Rajak et al. (2023), Rajak et al. (2018), Okoh et al. (2023), and Nigussie et al. (2020)
AI/Machine Learning	Random forest, neural networks, predictive analytics, disease detection algorithms, XGBoost, deep learning, transformer models, causal ML	Yield prediction, pest/disease forecasting, advisory systems, pattern recognition, crop type mapping, field boundary delineation	Mmbando (2025), Nturo et al. (2025), Liakos et al. (2018), and Foster et al. (2023)
Digital advisory platforms	Mobile apps, SMS services, climate information services, decision support tools, chatbots, USSD	Information dissemination, personalized recommendations, extension support, weather forecasting, market linkages	Shaibu et al. (2025), Thothela et al. (2021), Asante et al. (2024), and Abdulai et al. (2023)

need for training to enhance the potential of mobile phone technology in South Africa. Abebe F. et al. (2023) and Abebe G. K. et al. (2023) found that innovation platforms and soil monitoring tools achieved impacts only when accompanied by sustained institutional support.

Gender constraints create systematic exclusion (Leta et al., 2023; GSMA, 2022). Khoza et al. (2021) conducted a gender-difference analysis of CSA adoption in Malawi and Zambia using an extended Technology Acceptance Model and found that while perceived usefulness and ease of use did not differ significantly between men and women when controlling for access, structural barriers including land tenure security, restricted mobility, and unequal access to credit constrained women's adoption. In a similar pattern, Appiah et al. (2025) documented that women farmers have 30–50% lower access to digital agricultural services across Africa. Zougmoré and Partey (2022) found that gender-sensitive ICT interventions achieved higher adoption rates among women when designed with their specific constraints in mind.

Integration of indigenous knowledge emerged as a critical enabler (Oyelami et al., 2023). Thothela et al. (2021) conducted a study and found that the integration of indigenous knowledge with smart sensors and mobile technology enhanced decision support effectiveness and farmer acceptance. Bismark et al. (2021) compared farmers' perceptions of climate variability with meteorological and remote sensing data in Ghana, noting that the alignment between scientific and indigenous indicators increased trust and adoption. Shaibu et al. (2025) documented that farmers actively integrate both scientific forecasts and indigenous predictions in their decision-making, regarding them as complementary rather than competing sources of knowledge. Studies from West Africa, like Senegal, confirm similar patterns regarding the utilization of climate information (Beckie et al., 2022; Dibal et al., 2022).

3.7 The pilot-to-scale gap

A critical finding emerging from the synthesis is the persistent gap between successful pilot demonstrations and scalable, sustainable adoption (Kreft et al., 2023; Habiyaremye et al., 2024). Appiah et al. (2025) noted that among digital agriculture initiatives mapped across Africa, fewer than 10% had reached more than 10,000 farmers, and less than 5% were financially sustainable without donor support. Rurii and Nzengya Daniel (2026) identified this pilot-to-scale gap as a principal challenge, finding that most projects are designed as technological demonstrations rather than systematic interventions. Jellason et al. (2021) further emphasize that without addressing foundational infrastructure deficits, scaling remains elusive.

Choruma et al. (2024) conducted a scoping review of agriculture, documenting that pilots typically focus on technical efficacy while neglecting the infrastructural, economic, and institutional environments required for sustained operation. The result is a landscape of pilot projects demonstrating potential without lasting impact; that is, the project terminates when funding ends, technical staff depart, or maintenance needs arise (McFadden et al., 2022; Habiyaremye et al., 2024).

3.8 Practices and adoption outcomes

Table 5 presents a synthesized finding from the included studies on the influence of remote sensing, GIS-based tools, and the Internet of Things on smallholder farmers' decisions and climate-smart agriculture adoption rates.

TABLE 3 Technology application matrix.

Title	R/S	GIS	IoT	AI/ML
AI-Driven Precision agriculture for Smallholder Farmers in Rwanda: A Case Study in Kayonza District (Nturo et al., 2025)	✓		✓	✓
Smart IoT Framework for Climate-Resilient and Sustainable Maize Farming in Uganda (Nomugisha and Mwebaze, 2025)			✓	✓
A survey of Intelligent Agro-climate Decision Support Tool for Small-Scale farmers: An Integration of Indigenous Knowledge, mobile Phone Technology and Smart Sensors (Thothela et al., 2021)			✓	✓
Harnessing IoT and Data Analytics to enhance Resource efficiency and Crop Productivity in Smallholder Agriculture (Hope and Mwebaze, 2025)			✓	✓
Agro-ecological Lower Midland Zones IV and V in Kenya Using GIS and Remote Sensing for Climate-Smart crop Management (Manzi and Gweyi-Onyango, 2021)	✓	✓		
Harnessing artificial intelligence and remote sensing in climate-smart agriculture: The current strategies needed for enhancing global food security (Mmbando, 2025)	✓			✓
Precisions agriculture for resource use efficiency in smallholder farming system in Sub-Saharan Africa: A systematic review (Onyango et al., 2021)	✓	✓	✓	
Smart farming technologies for sustainable agriculture: A review of promotion and adoption strategies by smallholders in sub-Saharan Africa (Bashiru et al., 2024)	✓	✓	✓	✓
Agriculture 4.0: Is Sub-Saharan Africa Ready? (Jellason et al., 2021)			✓	✓
Adoption of ICT innovations in the agriculture sector in Africa: A review of the literature (Ayim et al., 2022)			✓	
IoT and machine learning-powered crop yield prediction system for smallholder farmers in Rwanda (Kuradusenge et al., 2024)			✓	✓
Utilization of Internet of things and wireless sensors network for sustainable smallholder agriculture (Bayih et al., 2022)	✓		✓	
Geographic information and communication technologies for supporting smallholder agriculture and climate resilience (Haworth et al., 2018)	✓	✓		
Internet-of-Things (IoT)-based smart agriculture: Toward making the fields talk (Ayaz et al., 2019)			✓	
Internet of Things in agriculture: Recent advances and future challenges (Tzounis et al., 2017)			✓	
Machine learning in agriculture: A review (Liakos et al., 2018)				✓
Digital technology and services for sustainable agriculture in Tanzania: A literature review (Mushi et al., 2022)			✓	
Agricultural land suitability analysis for maize crop by using GIS technology in case of Debub Gondar Zone, Ethiopia (Fetene, 2021)		✓		
A new maize variety adoption in Mozambique: A spatial approach (Fang and Richards, 2018)		✓		
Comparing farmers perceptions of climate variability with meteorological and remote sensing data: implication for climate-smart agriculture technologies in Ghana (Bismark et al., 2021)	✓			
Precision agriculture technologies for sustainable crop production in Ethiopia: A systematic review (Getahun et al., 2024)	✓	✓	✓	
Improving smallholder farmers' access to and utilization of climate information services in sub-Saharan Africa through social networks: A systematic review (Appiah et al., 2025)			✓	
Developing of IoT Cloud-based Platform for Smart farming in the Sub-Saharan Africa with Implementation of Smart-irrigation as Test-Case (Okoh et al., 2023)			✓	
Digitalisation in agriculture: A scoping review of technologies in practice, challenges, and opportunities for smallholder farmers in sub-Saharan Africa (Choruma et al., 2024)	✓	✓		
Digital innovations for climate-smart agriculture in East Africa: A systematic review (Zegeye et al., 2017)	✓	✓	✓	✓
IoT-Based Irrigation Management for Smallholder Farmers in Rural Sub-Saharan Africa (Nigussie et al., 2020)			✓	
Monitoring climate trends with remote sensing for evidence-based targeting of climate-smart agriculture technologies (Muthoni, 2023)	✓		✓	
Promoting the Adoption of Climate-Smart Agricultural Technologies Among Maize Farmers in Ghana (Asante et al., 2024)				✓
Digital Technology and Services for Sustainable Agriculture in Tanzania: A Literature Review (Mushi et al., 2022)		✓	✓	
The welfare of enhancing effects of agricultural innovation platforms and soil monitoring tools on farming households outcomes in southern Africa (Abebe G. K. et al., 2023)				✓
Digitization of African agriculture (Tsan et al., 2019)	✓		✓	✓
A review of applications of remote sensing toward sustainable agriculture in Northern savannah regions of Ghana (Moomen et al., 2024)	✓			

(Continued)

TABLE 3 (Continued)

Title	R/S	GIS	IoT	AI/ML
Evaluating utility of medium-resolution spatial Landsat 8 multispectral sensors in quantifying aboveground biomass (Dube and Mutanga, 2015)	✓			
Integration of optical and synthetic aperture radar imagery for cop mapping in Burkina Faso (Forkuor et al., 2014)	✓			
Spatial variability and mapping of soil fertility status in a high-potential smallholder farming area under sub-humid conditions in Zimbabwe (Soropa et al., 2021).	✓			
Analysis of land use/land cover changes and implications on crop production in South Africa (Wang et al., 2023)	✓		✓	
Examining the potential of sentinel-2 MSI spectral bands in estimating maize biophysical variables (Sibanda et al., 2015)	✓			
A GIS-based multi-criteria evaluation for rainwater harvesting suitability in Awi Zone, Northwestern Ethiopia (Fetene et al., 2026)		✓	✓	
Kenyan Counties Geospatial Data Knowledge to Monitor Crop Production (Wahome et al., 2023)		✓	✓	
Smart IoT-driven precision agriculture: Enhancing macro and micro nutrition efficiency and sustainability in modern agriculture and greenhouses (Pelekamoyo et al., 2026)				✓
Exploring the capability of high - resolution satellite data in delineating the potential distribution of common invasive alien plant species in the Tshivhase Tea Estate (Nembambula et al., 2023)	✓			
LoRaWAN-based IoT networks for smallholder agriculture in Kenya (Nigussie et al., 2020)				✓
GIS-based assessment of climate-smart agriculture adoption determinants in South Africa (Khoza et al., 2021)			✓	
Remote sensing and GIS for mapping agricultural drought vulnerability in Ethiopian highlands (Fetene, 2021)	✓		✓	
A framework for IoT-based precision irrigation for smallholder farmers in East Africa (Nigussie et al., 2020)				✓
The role of GIS in optimizing crop selection for climate-smart agriculture in South Africa (Fetene, 2021)			✓	
The digitization of agriculture in Africa: A scoping review (Choruma et al., 2024)	✓		✓	✓
Precision agriculture for smallholder farmers in sub-Saharan Africa (Onyango et al., 2021)	✓		✓	✓
The role of digital technologies in enhancing climate resilience among smallholder farmers in SSA (Mollel et al., 2025)	✓		✓	✓
GIS applications in agricultural extension services in Kenya (Ayim et al., 2022)		✓		
A review of practices of big data analysis in agriculture (Liakos et al., 2018)				✓
Internet of things for precision agriculture in sub-Saharan Africa (Tzounis et al., 2017)			✓	

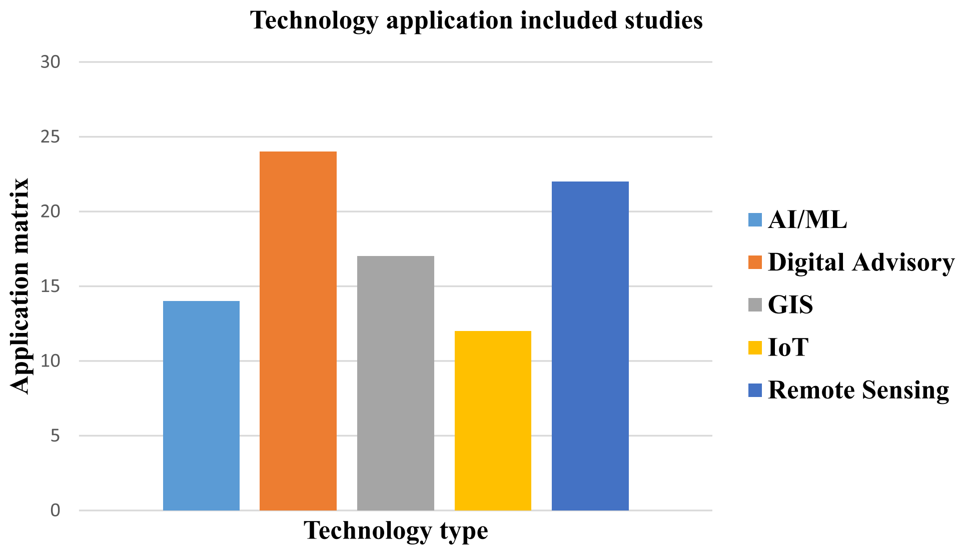

FIGURE 4
Technologies included in the study.

4 Synthesis

The synthesis of evidence from 56 studies across sub-Saharan Africa reveals a complex landscape in which remote sensing, GIS, and IoT technologies hold significant promise for transforming smallholder agriculture, yet their actual influence on farmer decision-making remains constrained by deep-rooted structural barriers. The key findings show a cohesive understanding of how these technologies

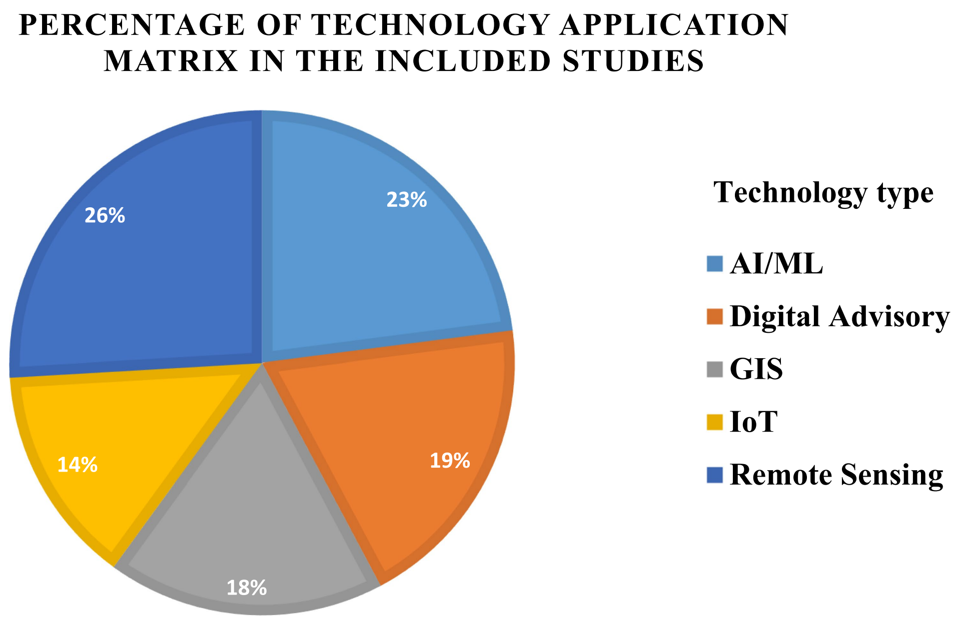

FIGURE 5
Technology application matrix by percentage.

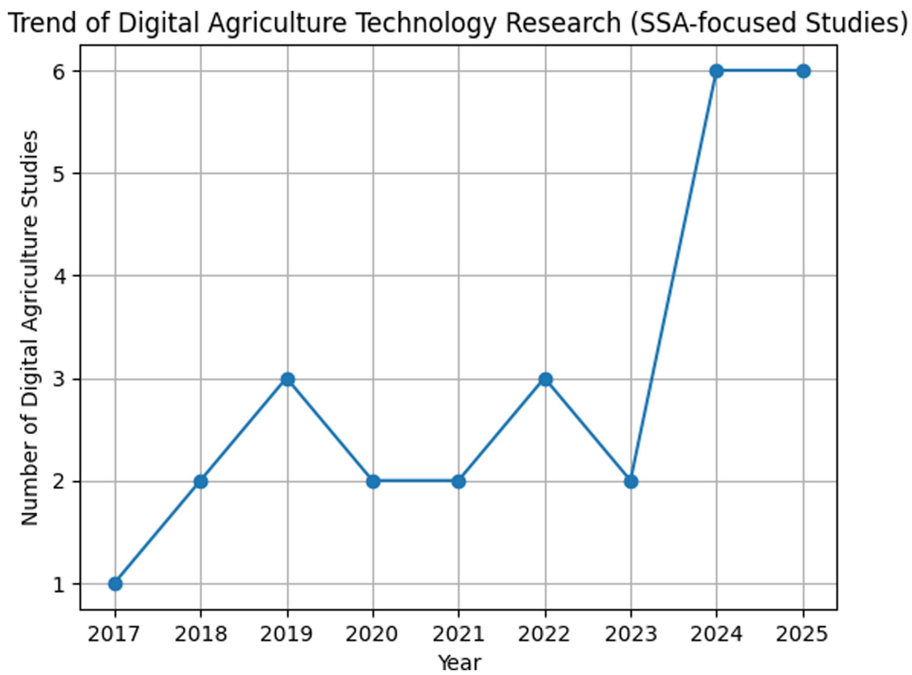

FIGURE 6
Digital agriculture technology trends in sub-Saharan Africa. The graph indicates the number of relevant publications per year plotted as a time trend.

function, their operational pathways, and the factors determining their adoption.

4.1 The influence pathways

Consistent evidence shows three distinct but integrated ways that digital technologies influence farmers' decision-making. These pathways formulate a unified framework that explains how these technologies inform action at different temporal and strategic scales.

Pathway 1–real-time information provision operates at the immediate level. IoT sensors, weather stations, and satellite imagery provide continuous streams of data that enable situational visibility. In this pathway, farmers who initially relied on guesswork are able to access precise information about when to irrigate their farms, the quantity of inputs such as fertilizers to apply to their crops, and whether the soil conditions are suitable for planting. Studies from Rwanda (Kuradusenge et al., 2024), Ethiopia (Bayih et al., 2022), Nigeria (Okoh et al., 2023), and Uganda (Nomugisha and Mwebaze, 2025) collectively demonstrate that when farmers receive timely, localized data, they make decisions that are more efficient, precise, and aligned with climate-smart principles. This pathway plays a fundamental role in shifting farmers' decision-making from traditional methods to evidence-based management.

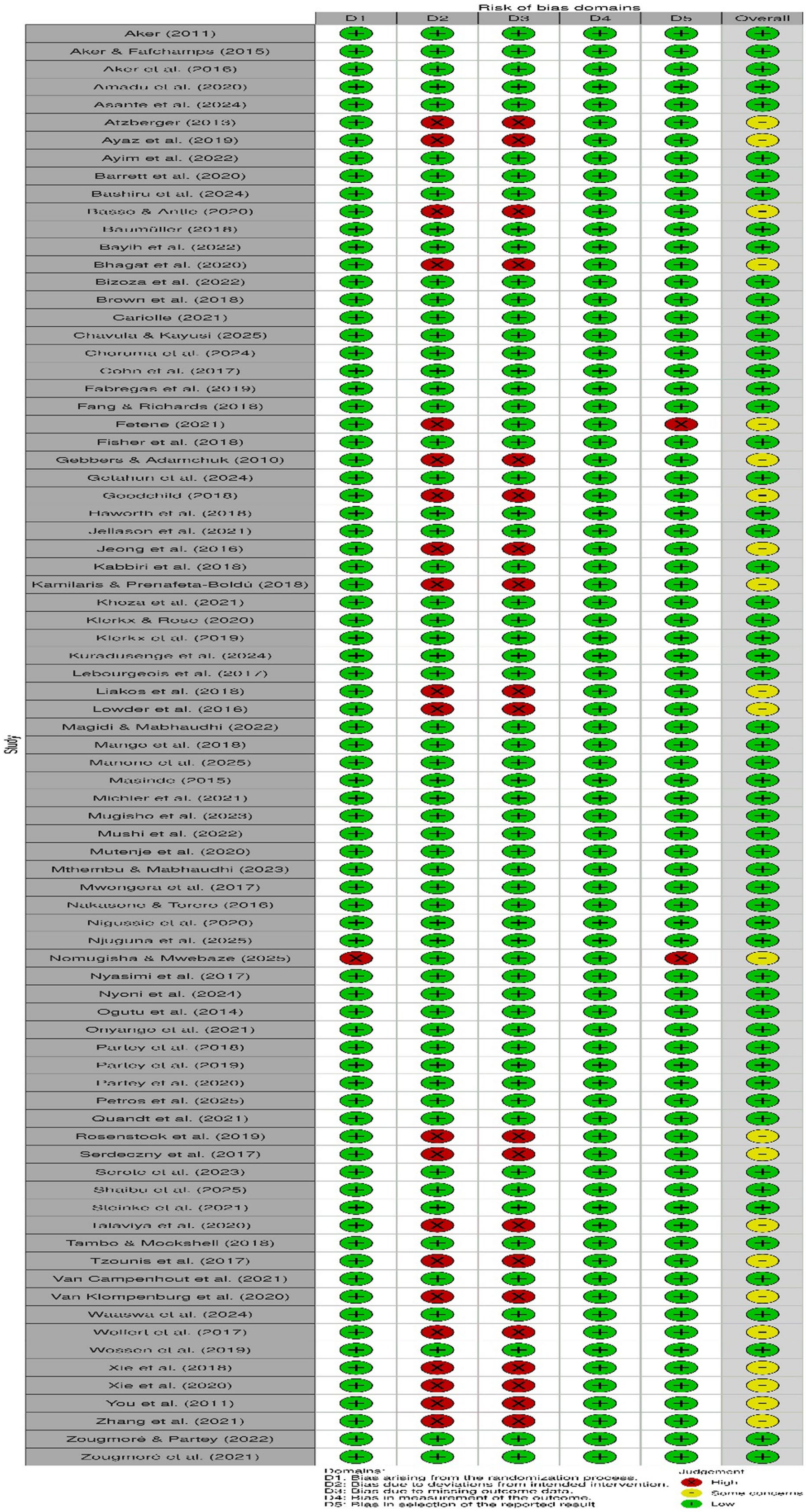

FIGURE 7
A visual representation of detailed risk of bias assessment (annexed).

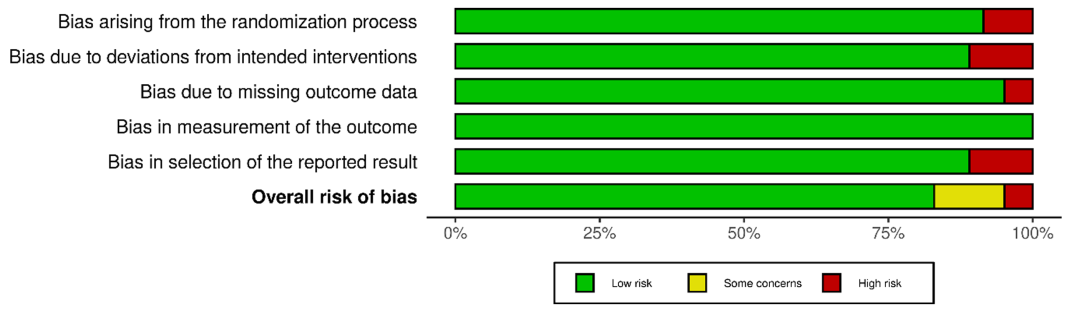

FIGURE 8
A summarized visual representation of risk of bias for included studies. Several studies rated as "some concerns" are foundational studies focusing on the digital technologies in question among smallholder farmers on a global scale.

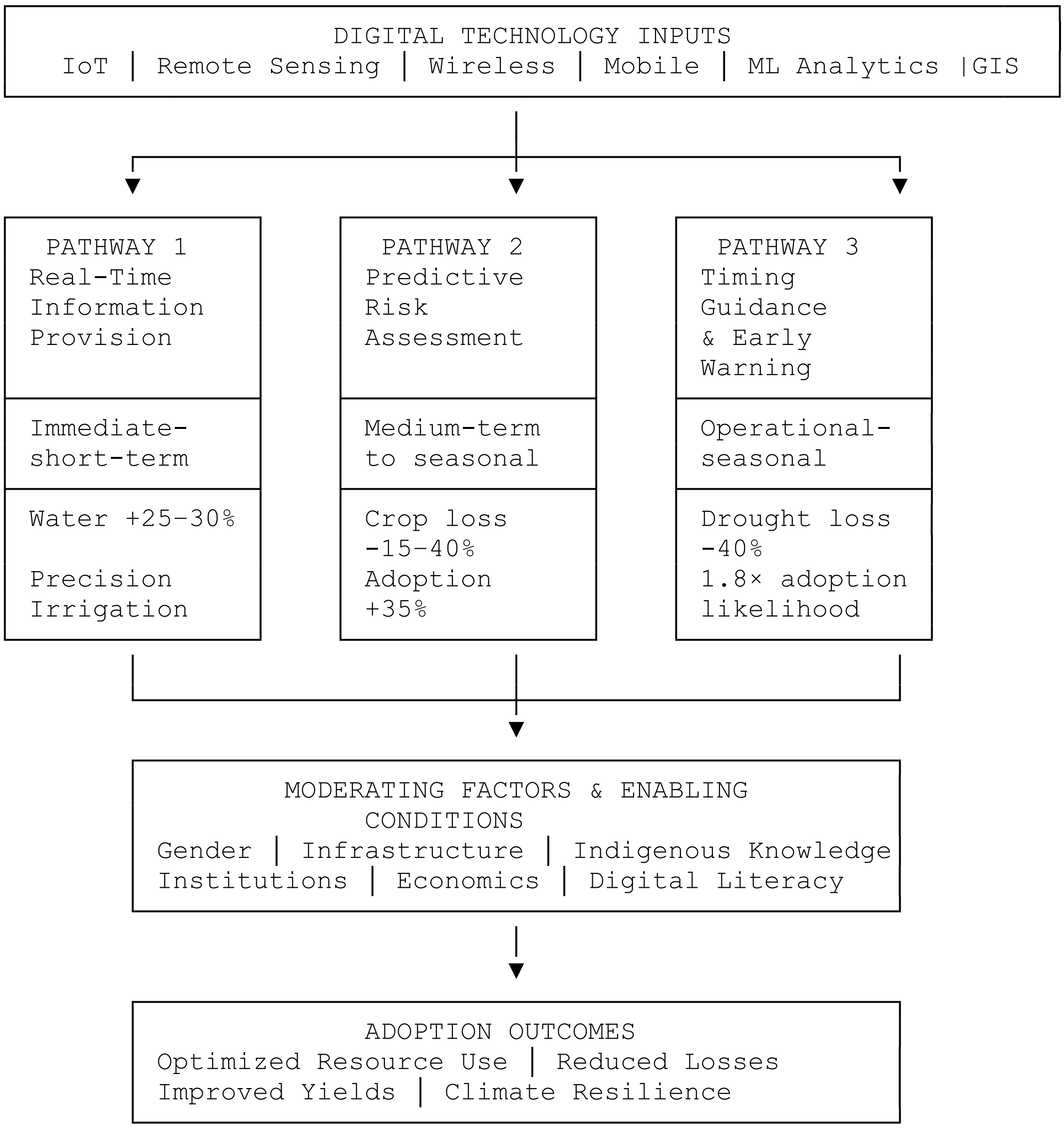

FIGURE 9
Integrated framework of digital technology influence pathways.

Pathway 2–risk assessment through predictive analytics operates at a strategic level. Machine learning algorithms applied to historical and real-time data forecast weather patterns, predict pest and disease invasions, and estimate crop yield prior to harvest. This information assists farmers in making informed decisions about crop varieties, planting times, and efficient resource use. Mmbando (2025) present a detailed review of how AI and remote sensing support early warning systems, whereas Shaibu et al. (2025) provide empirical evidence indicating

TABLE 4 Adoption determinants across studies.

Factor category	Enablers	Barriers	Representative studies
Technological	Real-time data availability, user-friendly interfaces, mobile compatibility, integration with indigenous knowledge, demonstrated effectiveness	High costs, technical complexity, maintenance challenges, lack of user-friendly design, incompatible platforms	Onyango et al. (2021), Kuradusenge et al. (2024), and Ayaz et al. (2019)
Infrastructural	Mobile network coverage, internet connectivity, access to stable electricity, LoRaWAN deployment, solar-powered solutions	Poor rural connectivity, unreliable power, high data costs, limited broadband infrastructure, network dead zones	Cariolle (2021), Jellason et al. (2021), and Tzounis et al. (2017)
Economic	Credit access, subsidies, household income diversification, off-farm income, cost-sharing mechanisms, pay-as-you-go mechanisms	High initial investment, poverty constraints, limited credit access, unaffordable data plans, unpredictable return on investment	Bashiru et al. (2024), Adenubi et al. (2021), and Onyango et al. (2021)
Institutional	Strong extension networks, training programs, government support, multi-stakeholder partnerships, farmer cooperatives	Weak extension systems, limited technical support, policy gaps, inadequate funding, project-based rather than sustained support	Ayim et al. (2022) and Abebe F. et al. (2023)
Social/ cultural	Farmer groups, social networks, alignment with local knowledge, peer learning, community champions	Resistance to change, mistrust of external information, language barriers, limited awareness	Thothela et al. (2021), Bismark et al. (2021), Shaibu et al. (2025), and Mthethwa et al. (2022)
Gender	Women's groups, gender-sensitive design, female extension agents, targeted training, flexible access models	Land tenure insecurity, restricted mobility, limited decision-making power, unequal access/ gender divide, time poverty	Khoza et al. (2021) and Appiah et al. (2025)

TABLE 5 CSA practices influencing technologies and adoption rates.

CSA practice	Adoption rate	Influencing technology	Representative study
Conservation agriculture	20–45%	Remote sensing for monitoring, GIS for sustainability mapping, IoT for soil moisture tracking	Brown et al. (2018), Partey et al. (2019), and Ariom et al. (2022)
Drought-resistant varieties	40–60%	Climate information, predictive analytics, remote sensing for variety matching	Shaibu et al. (2025), Petros et al. (2025), and Teklu et al. (2022)
Improved water management	20–50%	IoT sensors, smart irrigation, remote sensing for evaporation estimation	Kuradusenge et al. (2024), Bayih et al. (2022), Okoh et al. (2023), and Nigussie et al. (2020)
Agroforestry	15–35%	GIS for land suitability, remote sensing for monitoring, digital advisories	Partey et al. (2019), Zougmoré and Partey (2022), and Ewulo et al. (2025)
Integrated soil fertility	30–55%	Soil sensors, GIS mapping, digital advisory platforms, variable rate recommendations	Onyango et al. (2021)
Crop diversification	35–60%	Climate information, predictive analytics, market information systems	Amadu (2019), Waaswa et al. (2024), and Dadzie et al. (2024)

Adoption rates represent reported ranges across multiple studies; substantial variation exists based on context, technology type, and enabling environment.

that access to seasonal forecasts directly influences farmers' willingness to invest in climate-smart practices. This pathway transforms farmers from being reactive to proactive responders to climate shocks.

Pathway 3–timing guidance through optimized scheduling and early warning represents the most sophisticated integration of knowledge systems. It embodies a combination of local knowledge accumulated over time with modern sensor data and predictive analytics to generate specific recommendations about planting dates, irrigation timing, appropriate harvesting moments, and precise quantities of inputs to apply. The ITIKI system documented by Thothela et al. (2021) exemplifies this approach through a successful integration of indigenous drought indicators with artificial neural networks. Shaibu et al. (2025) further confirm that farmers do not choose between scientific and indigenous knowledge; rather, they actively integrate both, thus proving more effective in shaping their decisions. This pathway acknowledges that technology must complement, not replace, farmers' expertise. Put together, these pathways formulate a coherent framework crucial to understanding how digital technologies influence farmer decisions. For example, their operation, though different in time and scale (immediate, seasonal, and strategic), addresses different types of agricultural decisions. These technologies are not mutually exclusive in their operation; however, an effective intervention needs to integrate all three to create a comprehensive decision-support system that guides farmers from planning through execution.

4.2 Adoption determinant matrix: enablers and constraints

Whereas the pathways show the decision-influence mechanisms of these technologies, adoption determinants reveal why they do not (Teklu et al., 2022; Diro et al., 2022). This review synthesizes four categories of factors that collectively model adoption outcomes. These categories (infrastructural, economic, institutional, and gender) do not operate individually but constitute an interconnected system of hurdles to the influence of these technologies on farmers' decision-making.

Infrastructural barriers constitute the foundational constraint factor. Poor rural connectivity, high data costs, and unreliable electricity are more than mere inconveniences. Studies show that they are binding challenges that hinder technology uptake (Cariolle, 2021; Jellason et al., 2021). This indicates that, without network coverage, IoT sensors cannot transmit data; the absence of electricity jeopardizes the operations of weather stations, and unaffordable data hinders farmers' access to advisory services. The cumulative effect is that infrastructural deficits create a digital divide, contributing to the current geographic and economic marginalization.

Economic challenges complicate these infrastructural constraints. Even where infrastructure exists, the high costs of sensors, devices, and data plans place digital technologies beyond the reach of most smallholders (Bashiru et al., 2024; Onyango et al., 2021; Nigussie et al., 2020). For instance, a basic IoT sensor kit costing \$200–500 represents 3–6 months' income for the average household, making it unaffordable for many farmers. While access to credit and subsidies may alleviate some costs, their scarcity in rural areas remains widespread. These economic hurdles exert pressure that excludes the most needy—poor farmers who are highly vulnerable to climate risks—from the benefits of precision agriculture.

Institutional barriers cut across all categories, worsening systematic exclusion. Strong extension services, training programs, and continuous government support are catalysts for digital technology development and farmer adoption (Ayim et al., 2022). Nevertheless, evidence reveals frail extension systems, limited technical support, and disjointed policies across most sub-Saharan African countries. Even in situations where technologies exist, farmers lack effective training on their use and maintenance.

Gender constraints intersect with all other categories, creating systematic exclusion. Khoza et al. (2021) demonstrate that low adoption rates among women stem not from differences in perceived usefulness but from structural barriers such as land tenure insecurity, which limits decision-making power; restricted mobility, which hinders access to training; and skewed access to credit, mobile phones, and extension services. Appiah et al. (2025) confirm that women across Africa consistently have lower access to digital agriculture services. Furthermore, Mushi et al. (2022), in their systematic review on ICTs for climate resilience, documented that persuasive infrastructural and socio-economic barriers disproportionately affect the most vulnerable, including women. Therefore, gender acts as a multiplier of disadvantage that exacerbates all other barriers.

This synthesis recognizes that the decision to adopt technology is not determined by a single factor but through the interconnectedness of multiple challenges. A farmer may have access to credit (an economic enabler) but lack network coverage (an infrastructural barrier), hindering technological adoption for climate-smart agriculture. A female farmer may own a mobile phone (technological access) but lack decision-making power over land use (a gender barrier), inhibiting the practical application of technological services for climate-smart solutions. Thus, effective interventions must address this complexity through integrated approaches that simultaneously tackle multiple barriers.

4.3 Indigenous knowledge and technology integration

Multiple studies indicate the importance of incorporating indigenous knowledge with modern digital technologies not merely as a cultural sensitivity, but as a practical necessity to enhance effectiveness and adoption. Bismark et al. (2021), for instance, found that when scientific forecasts from remote sensing aligned with farmers' indigenous indicators, trust increased and adoption seamlessly followed. Similarly, Shaibu et al. (2025) documented that farmers actively integrate both knowledge sources in their decision-making processes, regarding them as complementary. The ITIKI platform, designed by Thothela et al. (2021) for integration, combines indigenous drought prediction with artificial neural networks and suggests technology design that begins with farmers' existing knowledge systems. This opens an opportunity for active participation from farmers in knowledge generation, a principle embodied in the citizen science approach.

4.4 Project-level pilot-to-scale as designed failure

This review suggests that the pilot-to-scale problem is fundamentally a design issue. The persistent gap between successful pilots and limited scaling, as documented by Rurii and Nzengya Daniel (2026), Appiah et al. (2025), and Jellason et al. (2021), reflects that most pilots are designed as technical demonstrations rather than systematic interventions. They focus on hardware and software while neglecting the infrastructural, economic, and institutional environments required for sustained operations. Projects are designed for efficacy demonstration rather than resilience and diffusion in real-world conditions of unreliable electricity, intermittent connectivity, limited technical support, and farmers with multiple competing demands.

Sustainable scaling requires designing for maintenance after funding ends, support after technical staff depart, adaptation to variable infrastructure, and affordability without subsidy. This necessitates building on existing institutions such as extension services, farmer cooperatives, and local businesses rather than creating parallel structures that collapse when project support withdraws.

5 Discussion

5.1 Limited but demonstrable influence

This review confirms that remote sensing, GIS-based tools, and IoT technologies have a demonstrable but limited influence on smallholder farmer decision-making for climate-smart agriculture adoption in sub-Saharan Africa. The evidence supports three primary conclusions: that technologies work under the right and favorable conditions, and that the three influencing pathways are empirically validated across multiple scenarios. The evidence indicates that in Rwanda, IoT-enabled precision irrigation changed farmers' decisions (Kuradusenge et al., 2024). Studies conducted in Ethiopia showed that real-time data delivered via mobile platforms influenced fertilizer application (Bayih et al., 2022), while in Ghana, seasonal forecasts shaped investments in drought-tolerant varieties (Shaibu et al., 2025). Similarly, Thothela et al. (2021) validated that the ITIKI system provided drought predictions that reduced crop loss in South Africa. Thus, in setups where infrastructure exists, training is provided, technologies are accessible, affordable, and designed for local contexts, the technologies positively influence farmer decisions.

Second, conditions are rarely right for farmers because infrastructure limitations, economic constraints, institutional weaknesses, and gender disparities exclude the majority of farmers from technological influence. Farmers who face high climate risks, especially in remote areas of the region, are excluded from the benefits of these technologies in CSA adoptions, thus creating a paradox in which the technologies that could help the most vulnerable are less accessible to them. Finally, the potential of these technologies is substantial but conditional, with evidence suggesting their appropriateness in the sub-Saharan Africa farming context; however, that potential might only be realized when accompanied by simultaneous investment in enabling environments that make them accessible and enhance their utility (Bashiru et al, 2024). Hence, the technologies are necessary but insufficient.

5.2 Vulnerability and exclusion paradox

The central paradox revealed by this review—farmers most vulnerable to climate change are those least likely to access the technologies that could help them adapt—operates through multiple mechanisms. Geographically, the most climate-vulnerable farmers often live in remote areas with the poorest infrastructure—precisely where IoT sensors cannot connect and satellites cannot substitute for ground-level validation. Economically, the most resource-poor farmers cannot afford the technologies that would make their resource use more efficient. Institutionally, farmers with the weakest extension links are least likely to receive training in technology use (Ayim et al., 2022). In addition, socially, women farmers who face the greatest climate vulnerability due to their dependence on natural resources have the least access to digital tools (Mushi et al., 2022; Khoza et al., 2021). This paradox poses a fundamental challenge to the premise that digital technologies can contribute to climate adaptation at scale. The point to note is that if technological influence remains concentrated among better-resourced, well-connected, and male-dominated populations, it will widen rather than bridge the existing inequalities. Such scenarios end up assisting those who need help the least while leaving behind those who actually need more help.

5.3 Infrastructure as prerequisite for technological deployment

The evidence from Cariolle (2021), Jellason et al. (2021), and Bashiru et al. (2024) establishes infrastructure as a binding constraint. In the absence of connectivity and data affordability, digital technology cannot function effectively, posing a profound challenge for intervention design. Too often, infrastructure is treated as an afterthought, while the evidence points out that it is a fundamental factor and must be regarded as a prerequisite investment; without it, technology deployment has no meaning. This means that digital agriculture interventions cannot succeed in isolation from broader rural development. The technologies require investment in grid extension, renewable energy, broadband deployment, and connectivity infrastructure. This insight shifts the responsibility from agricultural ministries alone to a multi-sectoral collaboration involving energy, telecommunications, and infrastructure development. It also suggests that the most impactful investment may not be in the technologies themselves but in the enabling systems that make technology effectiveness possible.

5.4 Indigenous knowledge as an asset

A significant findings of this review reveals the need to reframe indigenous knowledge vis a vis digital technologies (Oyelami et al., 2023; Ngulube, 2025). The literature consistently indicates that indigenous knowledge is not an obstacle to technology adoption but an asset that enhances it. Bismark et al. (2021) found that alignment between scientific and indigenous indicators increased trust, and Shaibu et al. (2025) documented that farmers integrate both knowledge sources. Thothela et al. (2021) and Abdulai et al. (2023) on the other hand, demonstrated that systems designed for integration achieve greater acceptance. These findings challenge the technology-centric approach that elevates modern technologies as a replacement for local expertise. They further suggest that effective intervention treats indigenous knowledge as an anchor for building solutions and not as a barrier to overcome in the development and deployment of these technologies. This has practical implications for technology design, such that algorithms can be trained on indigenous indicators. Interfaces could be designed to accommodate local classification systems, while advisory messages can be framed in terms that resonate with local understanding. The goal is not to replace farmer expertise with algorithmic authority but to augment it so that it provides farmers with better information without undermining their agency (Ngulube, 2025).

5.5 Gender as a multiplier hurdle

The gender analysis from Khoza et al. (2021), Appiah et al. (2025), Leta et al. (2023), and GSMA (2021) reveals that gender is not merely another variable but a multiplier of advantages that intensifies all other barriers. Female farmers face similar infrastructural, economic, and institutional constraints as men, but they experience these challenges more severely due to land insecurity, mobility restrictions, and unequal access to resources. Importantly, Khoza et al. (2021) found that when controlling for access, there is no difference in perceived usefulness and ease of use among male and female farmers. This indicates that women are not inherently resistant to technology; rather, they suffer systematic exclusion from access to these technologies and their enablers (GSMA, 2021; Leta et al., 2023). This perspective is supported by broader reviews on ICT adoption in Africa (Mushi et al., 2022; Ayim et al., 2022). The implication is that specific interventions designed to address structural barriers such as land rights, access to credit, mobile phone ownership, and extension contacts can bridge the gender gaps. The design of technology alone is insufficient and must thus be accompanied by social and institutional changes that reflect gender differences in the region (Leta et al., 2023).

5.6 Designed failure of pilot-to-scale as the problem

This review suggests that the pilot-to-scale problem is primarily a design problem (Habiyaremye et al., 2024; Kreft et al., 2023). For example, the existing gaps between successful and limited scale are documented by Rurii and Nzengya Daniel (2026), Appiah et al. (2025), and McFadden et al. (2022), showing that most pilots are designed as technical demonstrations. They overlook the evidence that the project cannot survive in a real world of unreliable electricity, intermittent network connectivity, limited technical support, and farmers having multiple competing demands. Thus, the pilots are designed for efficacy and demonstration rather than resilience and diffusion. It is evident that sustainable scaling requires design considerations that account for future maintenance after the end of funding, ongoing support after the retirement of technical staff, adaptation to various infrastructures, and affordability without subsidies. This requires building on existing institutions like extension services, farmer cooperatives, and local businesses, rather than creating parallel structures that crumble when project support is withdrawn (Habiyaremye et al., 2024).

5.7 Implications for policy and practice

The findings of this review have implications for policy and practice. For policymakers, the primary implication is that digital agriculture cannot be pursued in isolation from the broader rural development context. Infrastructure development does not merely complement technology deployment; rather, it is a prerequisite for technology. It is imperative that policies prioritize rural electrification, broadband deployment, and connectivity infrastructure alongside technology promotion. Policies need to address structural barriers such as land tenure inequalities, credit access, and extension reforms that shape adoption.

The review suggests implications for practitioners that technology design must begin with farmers and not sensors. This calls for investing time in understanding local knowledge systems, involving farmers in participatory design, and targeting interfaces with users before technology deployment. The design must consider affordability, exploring low-cost sensors, pay-as-you-go models, and shared access arrangements. This means integrating existing extension systems rather than bypassing their usefulness, training extension officers in technology use, and positioning technology as a tool for their work.

For researchers, there is a need for longitudinal research that tracks the technology's influence over multiple seasons, comparative studies that identify contextual factors shaping access and failures, and action research that tests interventions in real-world scenarios. The evidence heavily relies on pilot studies and cross-sectional surveys; thus, there is a need for research that tracks farmers over time and across contexts to understand what works where and why.

5.8 Limitations

This review acknowledges several limitations. First, uneven geographic coverage, with Eastern and Southern Africa overrepresented relative to Western and Central regions of sub-Saharan Africa. Central Africa's absence from single-country studies limits the generalizability of the findings across the region. Second, the peer-reviewed literature may have overrepresented successful pilots and underrepresented failures and implementation challenges, introducing public bias. Third, most studies are cross-sectional, limiting the understanding of sustained technology influence over multiple seasons. Fourth, the heterogeneity of technology types, outcome measures, and methodological approaches limits comparability across studies and precludes meta-analyses. Finally, the rapid evolution of digital technologies means findings may require updating as technologies and adoption patterns evolve. These limitations suggest the need for longitudinal research to understand the sustained potential impacts of these technologies on CSA adoption decisions across the region.

6 Conclusion

This systematic review confirms that remote sensing, GIS-based tools, and IoT technologies hold the potential to positively influence smallholder farmer decision-making for climate-smart agriculture adoption through well-documented pathways: real-time information provision, risk assessment through predictive analytics, and timing guidance via optimized scheduling. However, this influence is currently limited to small-scale piloting contexts and systematically excludes the most vulnerable farmers due to crosscutting infrastructural, economic, institutional, and gender barriers. The technologies operate under enabling conditions, which are evidently not available for most smallholder farmers. For these technologies to substantively contribute to climate adaptation, there needs to be a fundamental shift in approach from technology-centric interventions to systemic investment in enabling conditions that make technology accessible, affordable, and sustainable. This calls for viewing infrastructure as a prerequisite, indigenous knowledge as an asset, gender equity as central, and sustainability as a designed principle.

Without such systematic approaches, digital technologies risk widening the gap they purport to address and neglecting those who need help the most while assisting those who need them less. The promise of digital agriculture for climate adaptation in sub-Saharan Africa remains genuine but conditional: realized only when technology development proceeds hand-in-hand with the structural transformations that make its benefits accessible to all.

Author contributions

CO: Writing – original draft, Data curation, Formal analysis, Conceptualization, Methodology, Visualization, Investigation. EC: Conceptualization, Writing – review & editing, Validation, Supervision.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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